

DR

# DeepRob

Seminar 3

Object Pose, Geometry, SDF, Implicit Surfaces

University of Michigan and University of Minnesota



# This Week: Rigid Body Objects

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- Seminar 3: Object Pose, Geometry, SDF, Implicit Surfaces
  - 1. [SUM: Sequential scene understanding and manipulation](#), Sui et al., 2017
  - 2. [iSDF: Real-Time Neural Signed Distance Fields for Robot Perception](#), Oriz et al., 2022
- Seminar 4: Dense Descriptors, Category-level Representations
  - 1. [Dense Object Nets: Learning Dense Visual Object Descriptors By and For Robotic Manipulation](#), Florence et al., 2018
  - 2. [Normalized Object Coordinate Space for Category-Level 6D Object Pose and Size Estimation](#), Wang et al., 2019
  - 3. [kPAM: KeyPoint Affordances for Category-Level Robotic Manipulation](#), Manuelli et al., 2019
  - 4. [Single-Stage Keypoint-Based Category-Level Object Pose Estimation from an RGB Image](#), Lin et al., 2022

# Today: Object Pose, Geometry, SDF, Implicit Surfaces

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# SUM

Sequential Scene Understanding and Manipulation

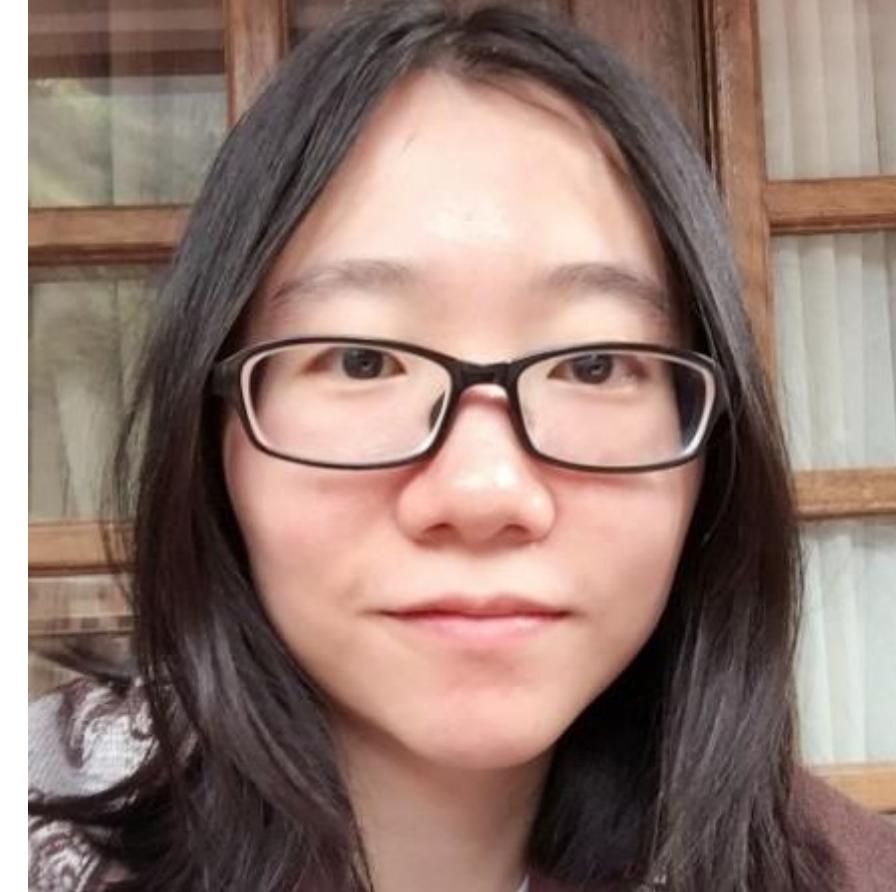
By: Zhiqiang Sui, Zheming Zhou, Zhen Zeng, Odest Chadwicke Jenkins

Presented by: Daniel Simmons



# The Handsome Authors

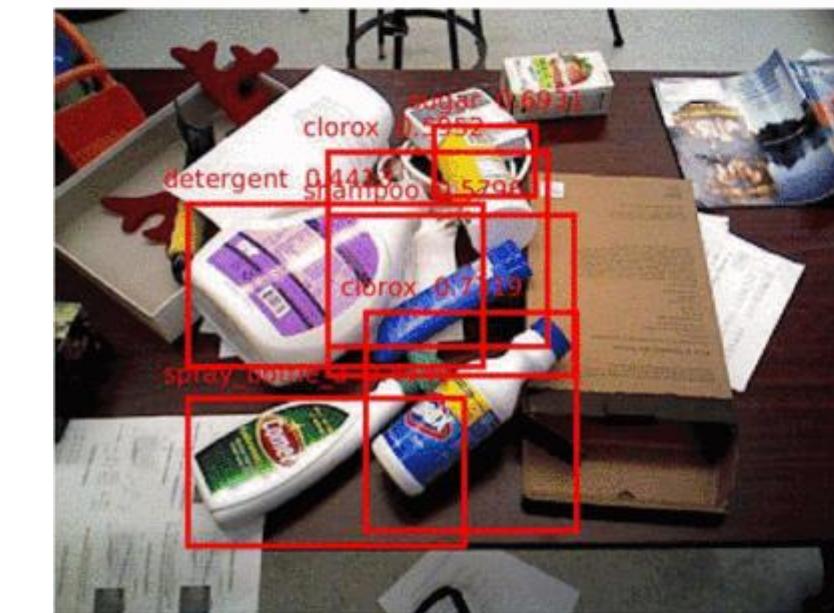
- Zhiqiang Sui
  - Former PhD Student at UMich
- Zheming Zhou
  - Former PhD Student at UMich
- Zhen Zeng
  - Former PhD Student at UMich
- Odest Chadwicke Jenkins
  - Professor at UMich



# Robots can't deal with this



- Need to find the cleaning items!



# Cleaning up the mess

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- Recognizing objects in cluttered environments is a critical challenge for a variety of tasks



- Video can be found at:  
<https://www.youtube.com/watch?v=ry0mqY5I-04>

# Addressing Limitations

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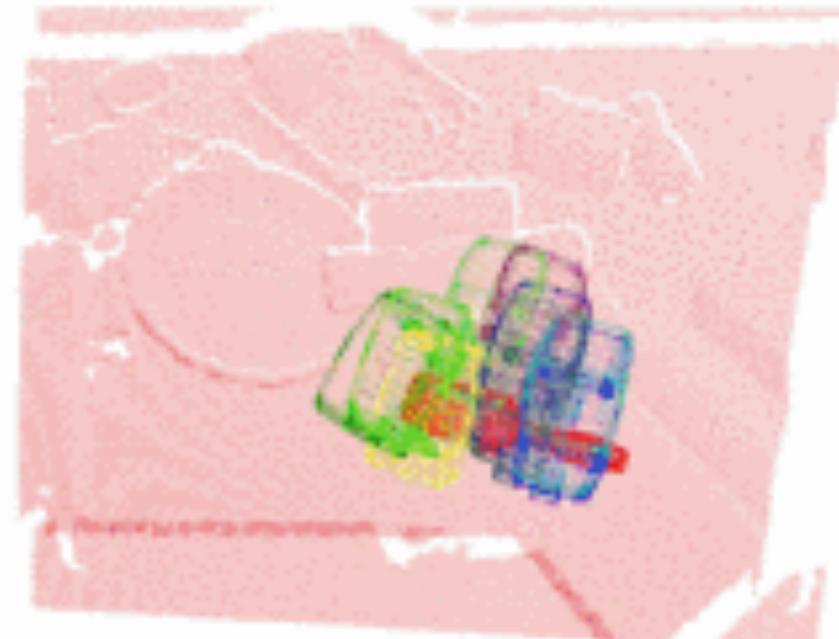
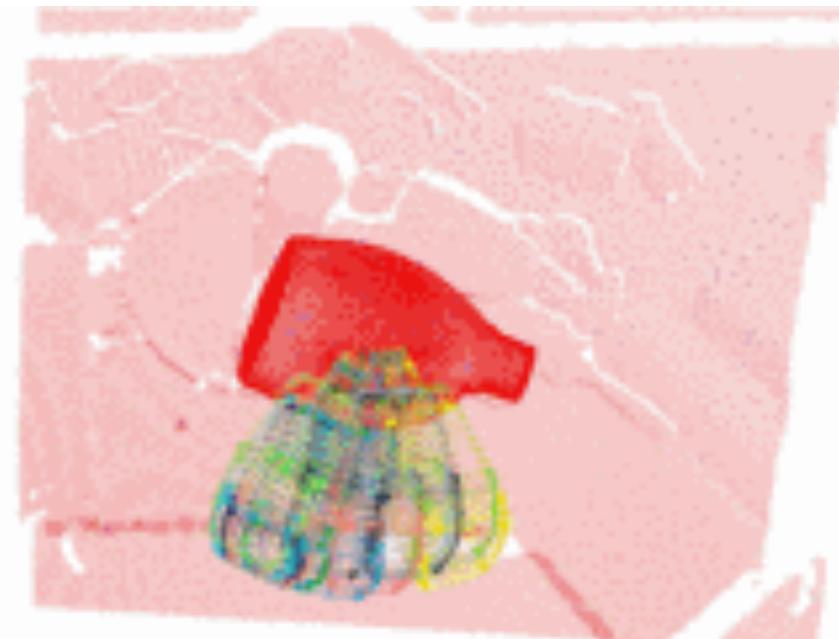
- Previous models assumed object detection was always accurate
- Objects were assumed to be static
- Generative methods were often used to predict layout

# Approach

1. Probability-evaluated object detection

2. Physics and state models

3. Pose evaluation

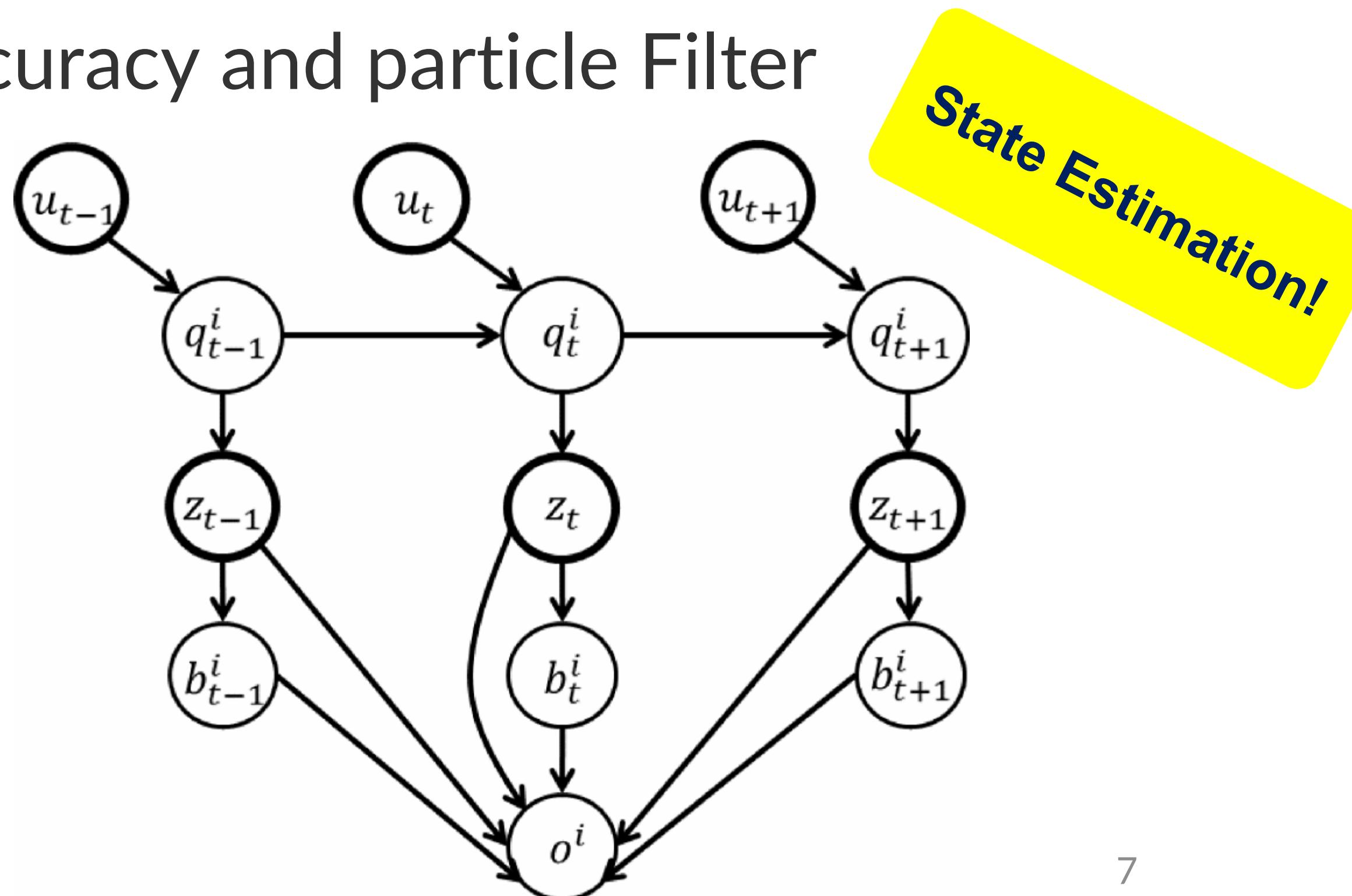


# State Estimation

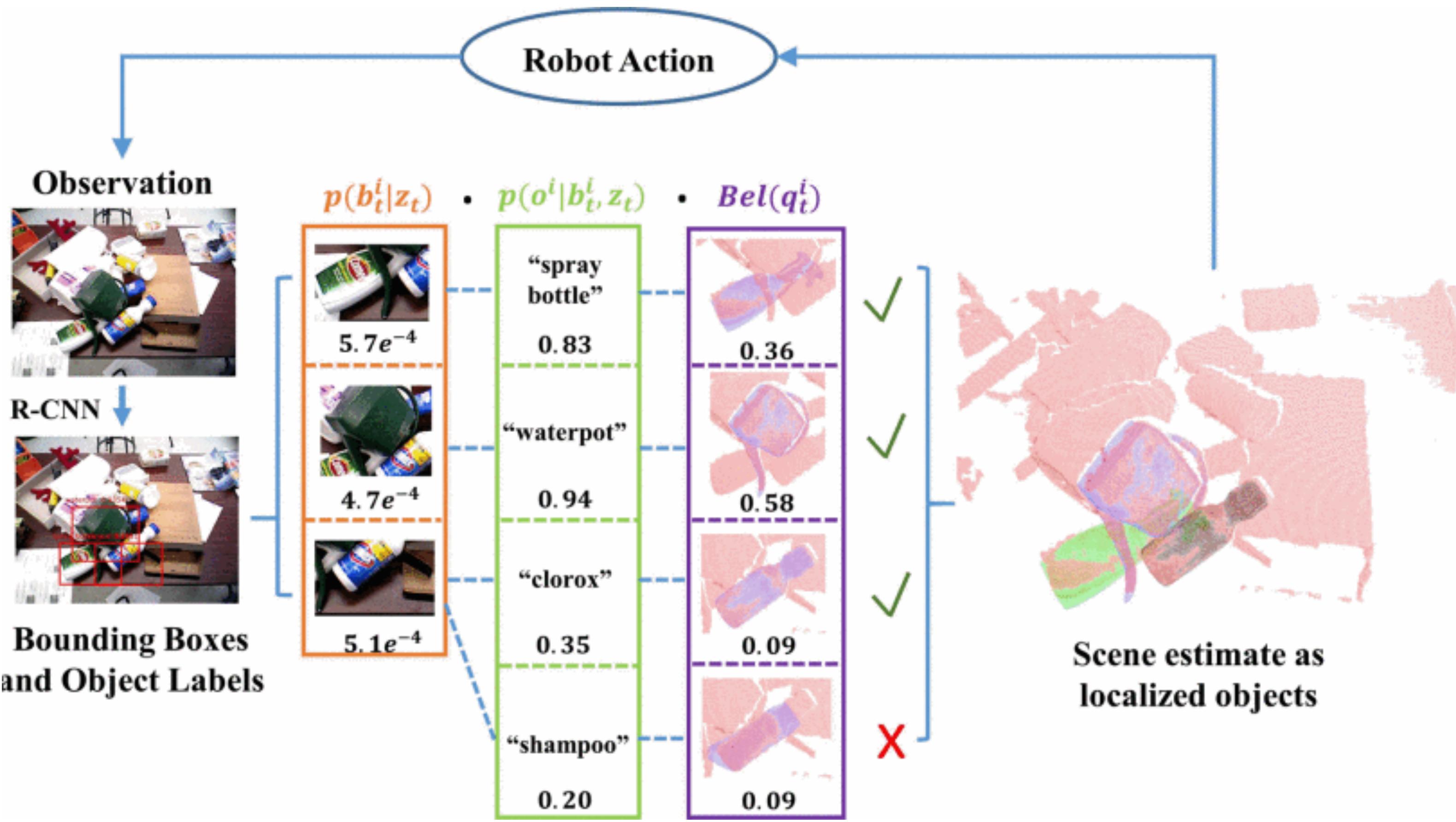
- Given **RGBD** observations estimate as objects with labels and poses
- Iterated with a bayes filter to assess accuracy and particle Filter

Probability!

$$p(x_t^i | z_{0:t}, u_{1:t}) = \underbrace{p(b_t^i | z_t)}_{detection} \underbrace{p(o^i | b_t^i, z_t)}_{recognition} \underbrace{p(q_t^i | b_t^i, o^i, z_{0:t}, u_{1:t})}_{Bel(q_t^i)}$$



# The Loop



# Trials

- 8 experiments with a Fetch Mobile Manipulation Robot
- 15 objects, 625 particles with 20 resampling iterations

Dataset



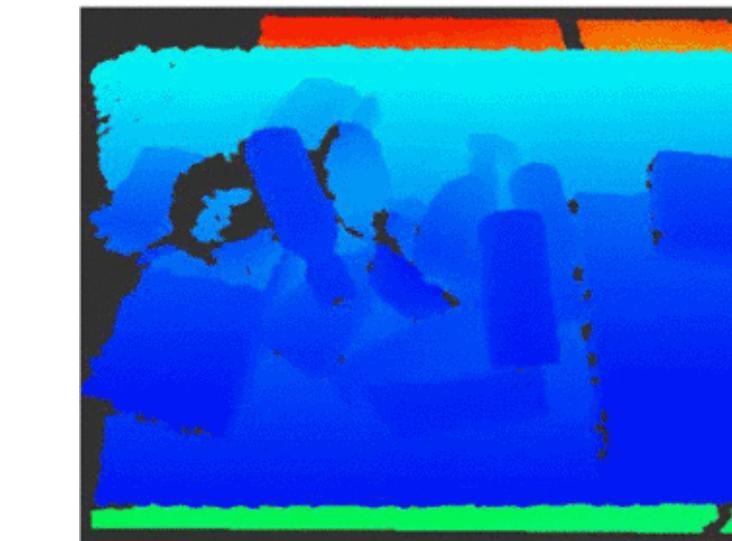
(a)

Clutter



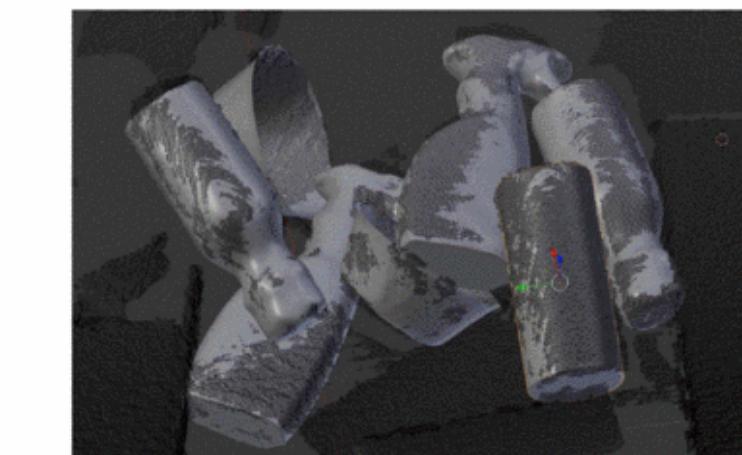
(b)

Depth Map



(c)

Ground Truth



(d)

# Sequence Table

	Sequence (a)	Sequence (b)	Sequence (c)	Sequence (d)	Sequence (e)	Sequence (f)	Sequence (g)	Sequence (h)
Number of total objects	5	5	5	5	5	5	5	5
Number of Manipulation Errors	1	1	2	0	0	1	1	0
Number of Manipulation Trials	4	6	7	5	5	5	6	5
Completion Ratio	0.80	1.0	1.0	1.0	1.0	0.8	1.0	1.0

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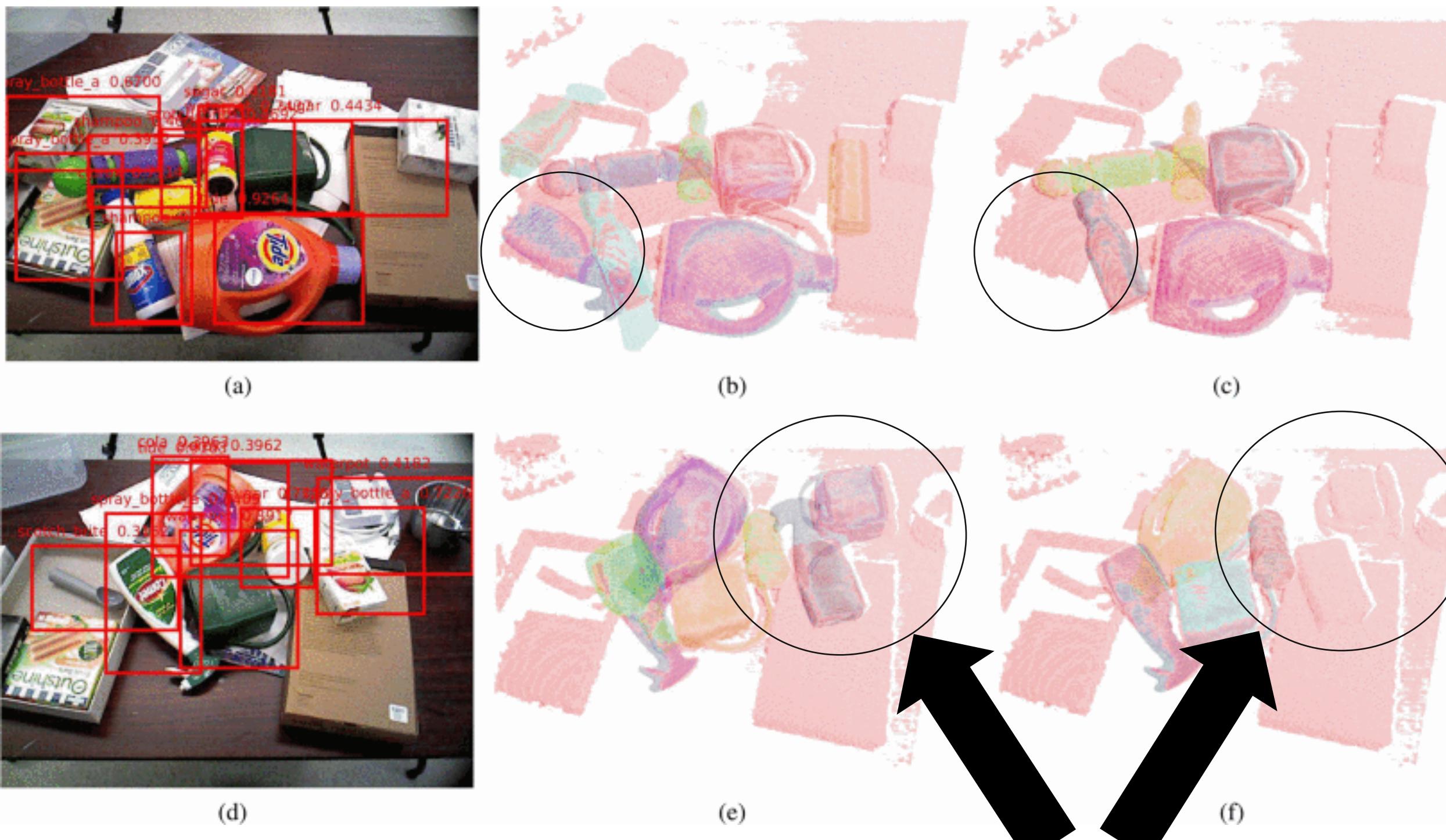
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# False Positives

- Able to overcome mistakes



- Object detection made mistakes
- Scene estimation recognized incorrect objects

# Conclusions

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- SUM is a generative and discriminative approach
  - Maintains belief over a sequence of actions
- Provides robust estimation and manipulation
  - Can parse and sort cluttered environments

# Limitations and Directions for Future Work

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- Limitations
  - Can solve for impossible joint positions
  - Frequent manipulation errors
- Future directions
  - Test with data other than RGBD
  - Apply motion to objects



Thank you





# Next Time: Dense Descriptors, Category-level Representations

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